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SELECTION OF WEARABLE SENSORS FOR HEALTH AND SAFETY USE IN THE CONSTRUCTION INDUSTRY

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Abstract. Construction industry workers; are exposed to serious safety and health risks, hazardous work environments, and intense physical work. This situation causes fatal and non-fatal accidents, reduces productivity, and causes a loss of money and time. Construction safety management can use wearable sensors to improve safety performance. Since there are many types of sensors and not all sensors can be used in construction applications, it is necessary to identify suitable and reliable sensors. This requirement causes a sensor selection problem. The study aims to determine the priority order of physiological and kinematic sensors in preventing risks in the construction industry. Within the scope of this purpose, five criteria and seven alternatives were determined in line with the literature research and expert opinions. The criteria weights were calculated with the AHP method, and the alternatives were ranked with PROMETHEE and AHP. Providing a proactive approach to the use of sensors in the construction industry will provide safer working conditions, identify workers at risk, and help identify and predict potential health and safety risks. It will contribute to the literature on improving construction health and safety management.

Keywords: occupational health and safety, construction industry, sensor, AHP, PROMETHEE.

Introduction

In the construction sector, which is considered a labor-intensive and dangerous occupation, the number of occupational injuries that cause loss of life or not is higher than in other sectors (International Labour Organization, n.d.). As it has been for years in Turkey, the most accidental deaths occurred in the construction sector in 2019. The number of workers who lost their lives in the work accident of 47,701 insured was 368 (Gözüak & Ceylan, 2021). Researchers and practitioners must combat the threat of occupational injury by focusing on identifying safety hazards and recommending proactive injury measures (Antwi-Afari et al., 2020). In the construction industry, employee fatigue, excessive physiological demands, and errors caused by physically demanding tasks can lead to potential risks such as injuries or accidents and a decrease in productivity in the long run (Gatti et al., 2014).

Workers can take precautions against hazards and risks by wearing appropriate personal protective equipment (PPE) (Kritzler et al., 2015). Many researchers have suggested using wearable sensor-based systems in the field of construction health and safety (Awolusi et al., 2018; Ahn et al., 2019; Häikiö et al., 2020). Various applications in the field of safety and health; include prevention of musculoskeletal disorders, prevention of falls, assessment of hazard recognition abilities, fatigue monitoring, and mental and physical workload assessment (Ahn et al., 2019). The foundation of construction project success, which deals with the complex interaction between humans, machines, and the surrounding environments, provides safe and healthy working conditions (Sato & Coury, 2009). Wearable devices can record real-time information that a person monitors about their movement activities and physiological state. Wearable sensor-based health monitoring systems can include flexible sensors that can be attached directly to the human body or different types of sensors that can be integrated into elastic bands, clothing, and textile fibers. Safety in the workplace is another area where wearable sensors and smart fabrics can play an essential precautionary role. Various risk situations through these systems, for example; it is possible to manage accidental

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falls, wrong posture, handling of loads with the wrong hand, and monitor fatigue levels as well as the worker's stress (Majumder et al., 2017).

In construction activity classification for construction workers, it is essential to identify a reliable and suitable sensor that aids in developing health and safety monitoring systems (Bangaru et al., 2020). In this study, the problem of prioritizing the kinematic and physiological sensors to prevent risks in construction is discussed in Turkey. The weights of the criteria; are prevention of falls, prevention of musculoskeletal disorders, evaluation of physical workload and fatigue, evaluation of hazard recognition abilities, and monitoring of the mental status of employees. Alternatives are listed as IMU, EMG, PPG, EDA, Eye Tracker, EKG, and EEG in both AHP and PROMETHEE methods.

As a result of the literature review, we have not encountered a study with the integration of AHP and PROMETHEE methods by addressing the ranking problem of the sensors in the construction sector to the best of our knowledge. The fact that it will be included in the first studies is essential in terms of contribution to the literature. Sensor selection is vital in construction, where labor-intensive production has more fatal and non-fatal accidents than in other industries. By determining the criteria weights of the most critical risks encountered in the sector, sensor selection is made. A proactive approach is presented. It will be helpful to identify the employees at risk, identify and predict potential health and safety risks, and close a significant gap in the literature on creating safe working conditions.

This article is organized as follows: The relevant scientific literature is included in Section 1, following the introduction. In Section 2, the methods used in the study and their steps are introduced. In Section 3, the modeling of the AHP and PROMETHEE methods used in the study is included, and an application has been made. The final section includes the results of the study and suggestions for future work.

1. Scientific literature review

Abdelhamid and Everett (2002) presented a comprehensive assessment of absolute physiological demands in construction work based on standardized work intensity tables to protect the safety and health of the workforce, increase productivity, and accept physiological limits to prevent long-term physical fatigue. Chang et al. (2009) how construction workers manifest the extent of physiological strain in different tasks before and after shifts at a high-rise construction site. They investigated steel fasteners, scaffolders, concrete workers, mold makers, electrician-plumbers, and various workers by making some physiological measurements, using demographic data and determining subjective fatigue symptoms. Wu et al. (2010) investigated the performance and feasibility of the sensor network by meeting, verifying, and analyzing the autonomous information requirement of accidents using a Zigbee RFID sensor network to prevent possible near-misses at construction sites. Kim & Nussbaum (2013) investigated the ability of a commercially available inertial motion capture (IMC) system to quantify exposures during five simulated manual material handling to reduce the number of physical exposures in the workplace over the long term. In their study, Khusainov et al. (2013) presented a holistic expression of the literature on sensor-based monitoring of daily activities and mobility as four main axes, applications, sensor types, and tracking device framework. Research gaps in the distribution of available studies by sensor types and applications, data collection, processing, and analysis, are identified as limitations and difficulties. They aim to prioritize future research directions by systematically presenting the literature study in the field wholly and systematically, facilitating the identification of research gaps. They aim to prioritize future research directions by systematically presenting the literature study in the field wholly and systematically, facilitating the identification of research gaps.

Yang et al. (2016) aimed to develop a method that automatically detects and documents near-misses based on the kinematic data of an employee obtained from Wearable Inertial Measurement Units (WIMU). Hwang et al. (2016) investigated the suitability of a PPG (Photoplethysmography; PPG) sensor embedded in a wristband tracker for construction use. Lee et al. (2017) aimed to monitor the usability and reliability of wearable sensors in the on-duty and off-duty activities of roofing workers. Majumder et al. (2017) presented a low-cost, non-invasive activity monitoring and health system. Maman et al. (2017) aimed to develop a task-independent, data-driven method through inexpensive wearable sensors that could be used to model physical fatigue. Nath et al. (2017) presented a low-cost, ubiquitous approach that uses built-in smartphone sensors to autonomously identify potential work-related ergonomic risks and discreetly monitor employee body postures.

Schal et al. (2018) investigated the potential benefits of using wearable sensors used by Occupational Health and Safety (OHS) specialists, especially personal activity monitors, in the workplace and the perceptions that hinder their adoption. Mardonova and Choi (2018) examined the classification of wearable devices and the characteristics of the sensors that can be attached to them. Cheung et al. (2018) aimed to improve the safety management of hazardous gas by integrating Building Information Modeling (BIM) and Wireless Sensor Network (WSN) technologies at an underground construction site. Awolusi et al. (2018) reviewed various applications of wearable technology for personalized trending and construction safety monitoring. Hwang et al. (2018) investigated the feasibility of measuring the emotions of field workers using a wearable EEG (electroencephalogram; EEG) sensor. Jebelli et al. (2018) proposed using a ready-to-use wristband-type wearable sensor to obtain the physiological signals of construction workers to assess their physical and mental state. In their study, they investigated the distinguishing power of three biosignals: skin temperature (ST), photoplethysmogram

(PPG), and electrodermal (EDA), in detecting the physical and mental states of workers while working on the construction site. Their results confirmed the applicability of the wristband-type wearable sensor to assess the mental and physical condition of construction workers.

Ahn et al. (2019) examined wearable applications in construction health and safety. Bangaru et al. (2020) evaluated the data quality and reliability of the inertial measurement unit IMU (Inertial Measurement Unit; IMU) of the armband and forearm EMG (EMG) sensors for construction efficiency classification. Antwi-Afari et al. (2020) proposed a non-invasive approach to identify safety hazards among construction workers to examine the feasibility of using workers' gait interruption models. Bangaru et al. (2021) proposed an automatic construction worker activity recognition method based on an Artificial Neural Network (ANN) that can recognize complex construction activities. Marra et al. (2021) proposed an innovative technique to demonstrate the feasibility of producing sensor fabrics. The strain sensor they made was found to engage in monitoring heart and respiratory rates. Stefana et al. (2021) investigated the wearable devices recommended for ergonomic purposes in the scientific literature and analyzed how they could support the improvement of ergonomic conditions. Antwi-Afari et al. (2022) aimed to automatically recognize and classify different types of inappropriate working postures in construction using deep learning-based networks and wearable insole sensor data. The study's findings revealed that it improves the health and safety of construction workers. Lee et al. (2022) developed a model to assess workers' exposure to slip, trip, and fall hazards by predicting abnormal gait patterns from a series of steps from a waist-mounted IMU sensor.

As a result of the literature review, we have not found a study in which the MCDM was applied, and the sensors were sorted to the best of our knowledge.

2. Materials and methods

In the study, which deals with the selection problem of kinematic and physiological sensors, alternatives and criteria were determined according to expert opinion and literature review. The criterion weights were made from MCDM with AHP, and the ranking of the alternatives was determined by AHP and PROMETHEE methods.

2.1. AHP method

It is concerned with information gathering, evaluation, decision making, and exchanges to analyze complex problems at all levels of an organization. Often these decisions are made through individual or collective judgment after weighing the advantages and disadvantages of policy options under conditions of uncertainty and risk (Saaty & Niemira, 2001). In the 1980s, Saaty developed AHP, one of the MCDM methods. AHP, a systematic decision-making method, includes qualitative and quantitative techniques. It helps obtain a single evaluation value based on different criteria or indicators. It simplifies the decision-making process by dividing a complex problem, where each element must be independent of the others, into a series of structural stages in the hierarchy of criteria (Saaty, 1980).

Decision-making is a process that includes the following steps (Saaty, 1990, 1994, 2008; Saaty & Niemira, 2001).

(1) Structuring the problem with a model that shows the essential elements of the problem and their relationships

A decision hierarchy is a structuring of goals from a broad perspective, by structuring above with the goal of the decision, then through the middle levels (criteria on which the next items depend) to the lowest level (usually a set of alternatives). Figure 1 shows the hierarchical structure.

(2) Creating a pairwise comparison matrix

In AHP calculations, pairwise comparisons are made between the decision elements in each component in terms of their importance according to the control criteria. The components are also compared in pairs for their contribution to the goal. Relative importance values are evaluated using the preference scale listed from 1 to 9 in Table 1.

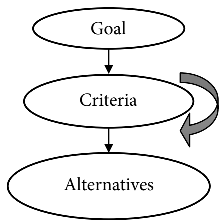


Figure 1. A hierarchy with interdependence (Saaty & Vargas, 1998)

Table 1. Significance scale values and definitions (Saaty, 2008)

Importance Level	Definition	Description
1	Equally important	Both options are equally important
3	Moderately important	Experience and judgment make one criterion slightly superior to the other
5	Strongly important	Experience and judgment favor one criterion over the other
7	Demonstrated dominance	One criterion is considered superior to the other
9	Extreme dominance	Evidence showing that one criterion is superior to another has great credibility
2, 4, 6, 8	Intermediate values	Values between two consecutive judgments to be used when reconciliation is needed

In the AHP method, the consistency ratio should be less than 0.10. If the value found is more significant than 0.1, the binary comparison matrix should be rechecked, and the steps should be repeated after the corrections are made.

(3) Determination of weights and ranking of alternatives

With the principle of hierarchical structure, the alternatives at the lowest level are ranked according to the general purpose of the highest level by obtaining their available weights.

2.2. PROMETHEE method

One of the MCDM methods is the PROMETHEE method. Jean Pierre Brans developed it in 1982. The partial ranking of the alternatives is presented with PROMETHEE I, while the full ranking is presented with PROMETHEE II (Brans & Mareschal, 2005). Advantages of this method over others; include the ability to determine qualitative quantities, the amounts of data that can be processed, configuring the problem, presentation on the GAIA plane, and good software support (Stefanović et al., 2019). The PROMETHEE method, which has been used for decades, continues to be renewed, and its ease of use has made it a standard method (Velasquez & Hester, 2013).

The method consists of five steps (Brans & Vincke, 1986):

1. The set of alternatives, the value of the alternative for each criterion, and the relative weight of each of the criteria are determined.
2. Based on criteria, the appropriate one of the standard preference functions are determined for the pairs of alternatives.
3. Preference indices are determined for each pair of alternatives.
4. Partial ranking is determined by PROMETHEE I, and positive and negative advantages are determined for alternatives.
5. PROMETHEE II determines the exact ranking for alternatives. The net advantage values and a full ranking for all alternatives are made by performing a total ranking for each of the alternatives.

3. Application

In the study in which the selection problem of kinematic and physiological sensors is discussed, the methodology of the problem is given in Figure 2.

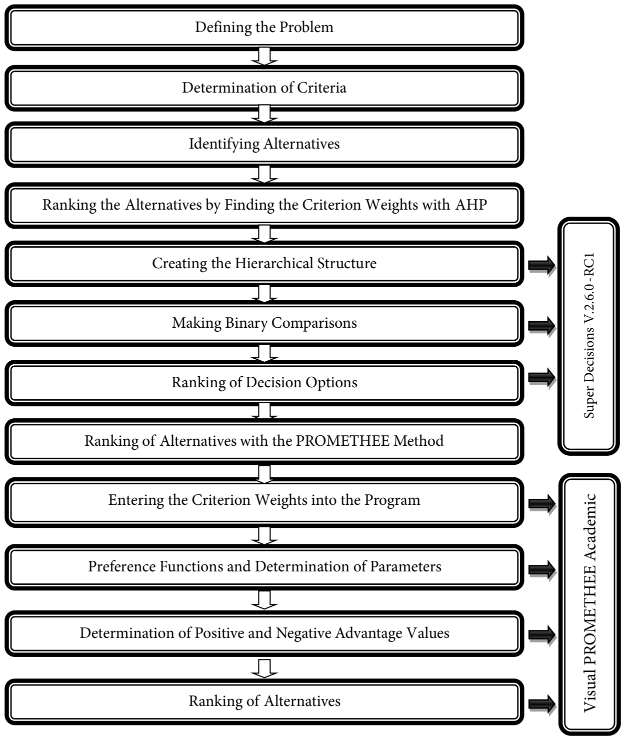


Figure 2. Flow chart of the problem

3.1. Problem definition

Construction projects; exposes workers to intense physical exertion, hazardous work environments, and serious safety and health risks. These risks cause an increase in the number of fatal and non-fatal accidents, paralyzing safety (Ahn et al., 2019). Poor occupational health and injuries caused by inadequate working conditions also affect the country's economy and the welfare of the working population (Valero et al., 2017). Ensuring high job security for employees is a top priority for employers (Bangaru et al., 2021). Within this priority, it is important to take proactive measures by preventing potential risks such as fatigue, injury, or accident for workers in the construction sector, which is a labor-intensive industry.

The construction workforce is exposed to life-threatening and non-life-related injuries due to the lack of appropriate safety training and monitoring systems. Various researchers have stated that wearable sensor-based systems would be suitable for use in construction health and safety to cope with the existing challenges (Hwang et al., 2018). Determining the priority order of physiological and kinematic sensors, which are among the sensor types, in preventing risks in construction has been considered a problem. Alternatives and criteria were determined in line with expert opinions and literature review. Calculating the criterion weights was done by the AHP method, and the ranking of the alternatives was made by the AHP and PROMETHEE methods.

3.2. Determination of criteria

According to the literature and expert opinion, the criteria in the prevention and evaluation of risks of sensors used in construction safety and health; are preventing falls, evaluating physical workload and fatigue, preventing musculoskeletal disorders (improper posture, repetition, vibration, etc.), monitoring of the mental status of employees, evaluation of hazard recognition abilities (Schall et al., 2018; Awolusi et al., 2018; Jebelli et al., 2018; Ahn et al., 2019).

3.3. Identifying alternatives

In the study, in which the kinematic and physical sensors used to prevent risks in construction are considered as the selection problem, Inertial Measurement Unit (IMU), electrocardiogram (ECG), photoplethysmogram (PPG), electrodermal activity (EDA), eye tracking, which is widely used especially in construction safety and health, electromyography (EMG), electroencephalogram (EEG) alternatively according to the literature (Hwang et al., 2016; Majumder et al., 2017; Awolusi et al., 2018; Mardonova & Choi, 2018; Ahn et al., 2019; Bangaru et al., 2021) determined.

Inertial Measurement Unit (IMU) Sensor: IMU is widely used in the construction industry as a wearable sensor to measure the kinematic motion of objects, including construction workers, equipment, and tools (Bangaru et al., 2021). IMU sensors are worn on employees' bodies; they are used to determine workers' body posture, acceleration, and orientation (Kim & Nussbaum, 2013). The application of IMUs to monitor human movement is becoming popular as part of the ergonomic evaluation that does not significantly disrupt employees' work performance (Stefana et al., 2021). Gait analysis has been used to assess fall risk in construction environments. Given that trips, falls, and slips can be caused by poor interactions between the ground and the foot surface, monitoring a worker's foot movement during successive walks provides information on the impact of internal (e.g., fatigue) and extrinsic (e.g., job site hazard) factors. On a worker's fall risks, IMUs placed at waist level or the lower body provided gait parameters (e.g., distance, stride duration) or gait stability metrics to capture disruptions in a worker's gait pattern (Ahn et al., 2019).

Photoplethysmography (PPG) Sensor: A PPG sensor is used for heart rate monitoring, which consists of light-emitting diodes (LEDs) based on spectrographic technology and a photodetector for optical detection of blood flow rate caused by heart activity (Hwang et al., 2016).

Electromyography (EMG) Sensor: It captures muscle load used for ergonomic evaluation and muscle activity used to evaluate forces (Nimbarte et al., 2010).

Electrocardiogram (ECG) Sensor: Cardiac activity measurement facilitates the determination of the physiological status of workers. Measurements of heart rate variability, heart rate variability, and heart rate reserve derived from heart rate are vital in determining employees' physical and mental state (Hwang et al., 2016; Jebelli et al., 2018).

Electroencephalogram (EEG) Sensors: It is used to assess the mental state of workers in the workplace and the effectiveness of training programs (Jebelli et al., 2019).

Electrodermal Activity (EDA): EDA has been widely used in security research to measure perceived risk because activities in the sympathetic nervous system stimulate perceived risk (Herrero-Fernández, 2016; Schmidt-Daffy 2013).

Eye Tracking: Using eye-tracking to measure eye movements and positions relative to the participant's head helps evaluate hazard recognition skills and construction safety training (Hasanzadeh et al., 2017).

3.4. Ranking the alternatives by finding the criterion weights with AHP

The AHP method was used in the study in which five criteria and seven alternatives were determined. Super Decision V.2.6.0-RC1 program was used in AHP calculations. The display of the hierarchical structure is given in Figure 3.

Pairwise comparisons were made with the group decision of 7 expert decision-makers, consisting of a class A occupational safety specialist, an academician in the field of occupational health and safety, and five academicians working in the field of occupational health and safety expert decision-makers were asked to respond to pairwise comparisons according to Saaty's 1–9 scale in Table 1.

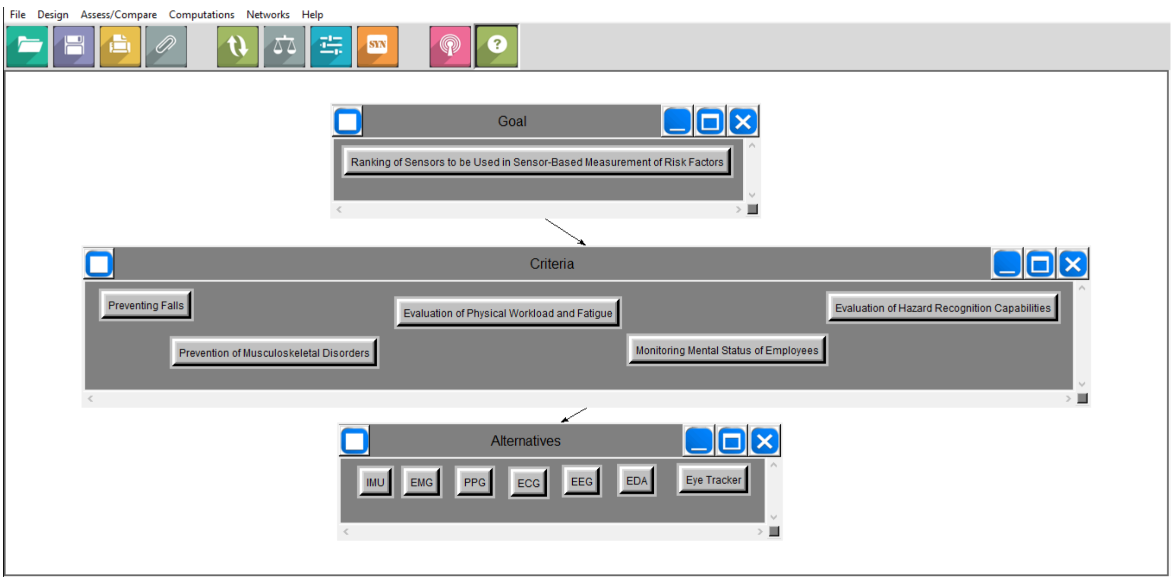


Figure 3. Hierarchical structure of the decision problem

In all paired comparisons created, the condition that the consistency ratio is less than 0.1 was met. An example comparison from the pairwise comparisons made in Figure 4 is given.

In Figure 5, the weights of the criteria obtained by the AHP method using the Super Decision Program and the ranking of the alternatives are given.

3.5. Ranking of alternatives with the PROMETHEE method

In our study, EMG, IMU, EDA, ECG, Eye Tracker, PPG, and EEG will be determined as alternatives and ranked by the PROMETHEE method. The criteria weights obtained by the AHP method were entered into the Visual PROMETHEE Academic Version Program. Table 2 contains the preference functions for problem-solving (Brans & Mareschal, 2005). In our study, the First Type (Ordinary) Function, one of the preference functions, was used. While PROMETHEE Data Entry is presented in Figure 6, the alternatives are listed in Figure 7.

With the PROMETHEE Method in Figure 7, which is the result of the solution, phi+ positive superiority values, phi- negative superiority values, and the difference of positive and negative superiority values in the ranking of the alternatives show the phi net priority value.

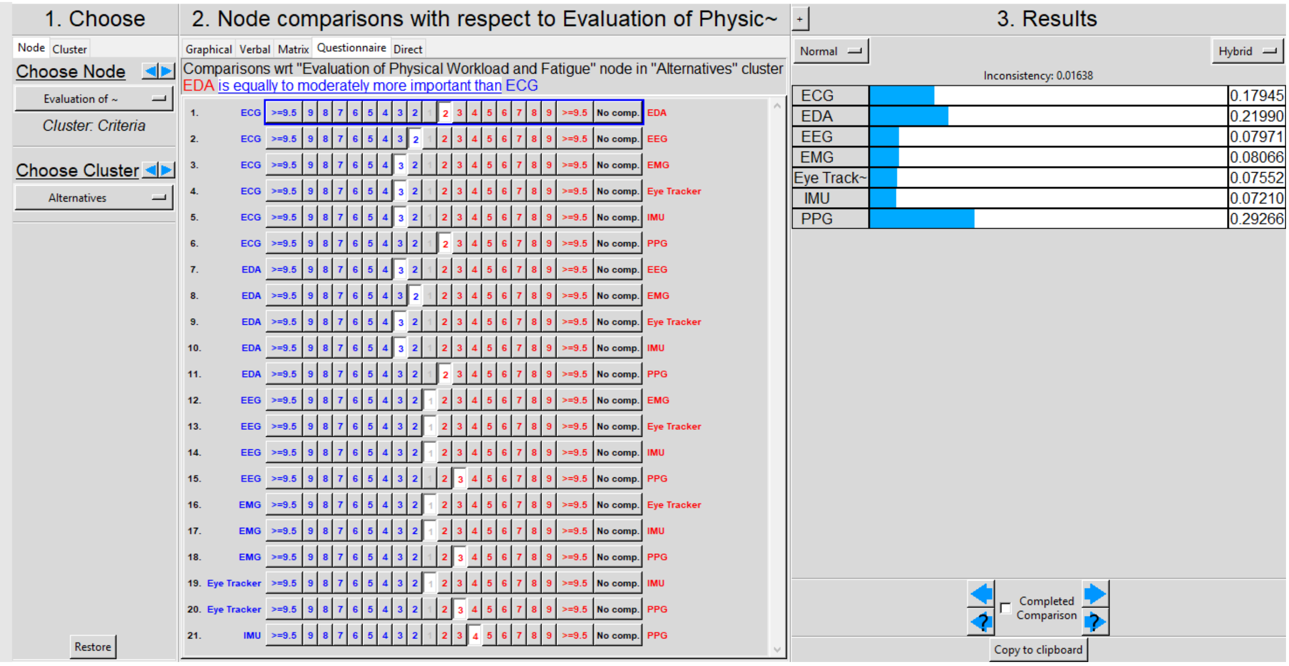


Figure 4. Pairwise comparison

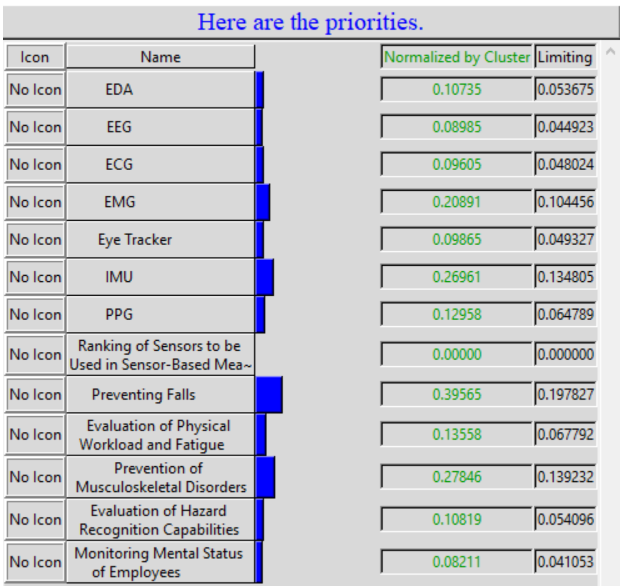


Figure 5. Criterion weights and ranking of alternatives

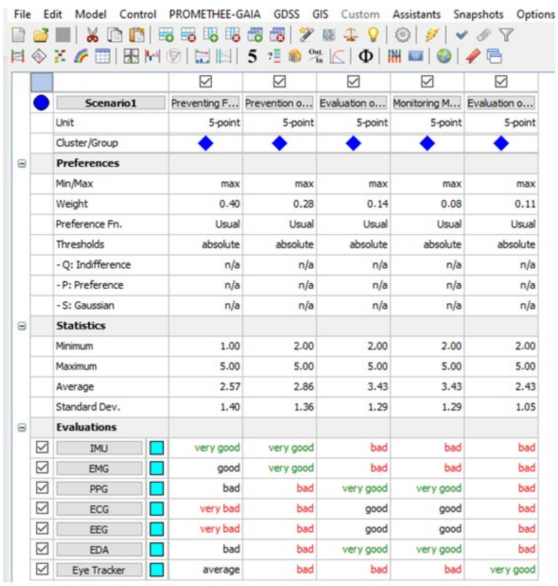
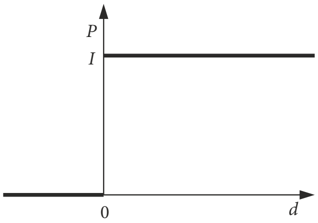
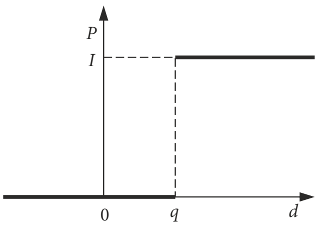
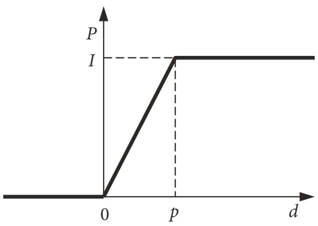
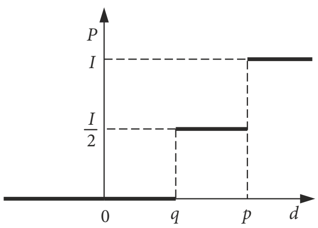
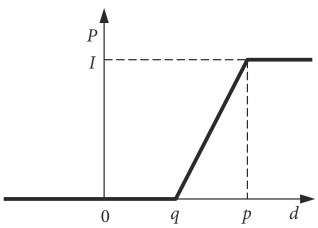
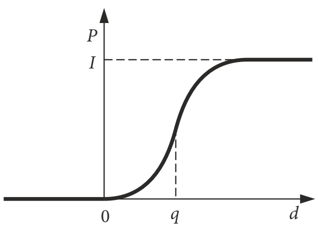


Figure 6. PROMETHEE data entry

Table 2. Preference functions (Brans & Mareschal, 2005)

Generalised criterion	Definition	Parameters to fix
Type 1: Usual Criterion 	$P(d)=\begin{cases}0 & d\le 0\\ 1 & d>0\end{cases}$	–
Type 2: U-shape Criterion 	$P(d)=\begin{cases}0 & d\le q\\ 1 & d>q\end{cases}$	q
Type 3: V-shape Criterion 	$P(d)=\begin{cases}0 & d\le 0\\ \dfrac{d}{p} & 0\le d\le p\\ 1 & d>p\end{cases}$	p
Type 4: Level Criterion 	$P(d)=\begin{cases}0 & d\le q\\ \dfrac{1}{2} & q<d\le p\\ 1 & d>p\end{cases}$	p, q
Type 5: V-shape whit indifference Criterion 	$P(d)=\begin{cases}0 & d\le q\\ \dfrac{d-q}{p-q} & q<d\le p\\ 1 & d>p\end{cases}$	p, q
Type 6: Gaussian Criterion 	$P(d)=\begin{cases}0 & d\le 0\\ 1-e^{-\frac{d^2}{2s^2}} & d>0\end{cases}$	s

PROMETHEE Flow Table

Rank	action	Phi	Phi+	Phi-
1	IMU	0.4645	0.6277	0.1632
2	EMG	0.3327	0.5618	0.2291
3	PPG	0.0046	0.3133	0.3087
3	EDA	0.0046	0.3133	0.3087
5	Eye Tracker	0.0021	0.3720	0.3698
6	ECG	-0.4043	0.1088	0.5131
6	EEG	-0.4043	0.1088	0.5131

Figure 7. Ranking of alternatives by PROMETHEE method

Alternatives are ranked according to their net priority values. Ranking by positive superiority was ranked as IMU, EMG, Eye tracker, PPG and EDA, ECG, and EEG. According to negative superiority, ECG and EEG, Eye tracker, PPG and EDA, EMG, and IMU are ranked. The final ranking is obtained with the net priority value. In this order, the alternatives are; IMU, EMG, PPG, and EDA are listed as Eye tracker, ECG, and EEG.

Conclusions

This study discusses the problem of determining the priority order of physiological and kinematic sensors in preventing risks to construction safety and health. Five criteria and seven alternatives were identified. AHP and PROMETHEE methods were used to solve the problem. The weights of the criteria obtained following the expert opinion with the AHP method; prevention of falls (0.39564), prevention of musculoskeletal disorders (0.27846), assessment of physical workload and fatigue (0.13558), assessment of hazard recognition abilities (0.10819), monitoring of the mental status of employees (0.08211) sorted as. Alternatives are listed as IMU, EMG, PPG, EDA, Eye Tracker, ECG, and EEG with both AHP and PROMETHEE methods. IMU sensors have emerged as the most crucial alternative for preventing falls with the highest criterion weight and preventing musculoskeletal disorders. The EMG sensor, essential in evaluating muscle load and forces used for ergonomic evaluation, followed the IMU. PPG and EDA sensors, which are particularly effective in assessing physical workload and fatigue, and preventing many risks by monitoring the mental state of employees, ranked third and fourth. The eye tracker, which helps assess hazard recognition skills and construction safety training, ranked fifth. This sensor was followed by ECG and EEG sensors used to evaluate the physical and mental states of the employees.

Safety and health; Ensuring quality and productivity is indispensable for positively affecting business performance. The data obtained through sensors for health and safety must be processed and used to prevent employee injury. By providing safer working conditions with the study, using sensors to detect employees at risk in this sector will help identify and predict potential health and safety risks by providing a proactive approach. In the future, a comparative ranking can be made using different MCDMs for environmental and location monitoring sensors in the construction industry.

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